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Published in:
Proceedings of the 13th International Conference on Applications of Statistics and Probability in Civil Engineering, ICASP 2019

Publication date:
2019

Document Version
Publisher's PDF, also known as Version of record

Probabilistic Evacuation Assessment with Real-time Monitoring Information

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ABSTRACT: The present paper proposes a probabilistic modeling approach for assessment and decision support of tactical loss reduction for roadway tunnel systems subject to fire events. The proposed probabilistic modeling approach combines scenario-based risk models for the probabilistic representation of accidents and fires with agent-based probabilistic representations of the escape scenarios of persons. The Fehmarn-belt tunnel is used as case study and a real-time daily traffic (RTDT) curve is considered. The vehicle population and the number and categories of persons in individual vehicles are modelled probabilistically based on statistics from the European Union. The example focuses on the modelling and assessment of the effects of tunnel closure, as a risk reducing measure in case of fire, on the evacuation dynamics. The results show that fast hindrance of traffic entry into the tunnel system efficiently reduces the expected value of the number of exposed persons but at the same time increases the variance associated with the number of persons evacuated within a given time frame.

1. INTRODUCTION

Research on the modeling of fire incidents in tunnel systems from a deterministic perspective focusses on aspects such as evacuation dynamics [Ronchi et al. 2012 and 2013], effects of ventilation systems [Króla et al. 2017], emergency systems [Capote et al. 2013] as well as computational fluid dynamics modelling and the influence of fire characteristics [Vidmar et al. 2017]. Research on probabilistic modelling of fire incidents is typically directed on the representation of the accident scenarios leading to fire events taking basis in the findings of deterministic research; see e.g. Schubert et al. 2011 and ASTRA 89005.

In fire risk assessment of roadway tunnels, the consideration of real-time information on tunnel operations and associated uncertainties is important in order to identify efficient first response risk reducing measures. In the case of fire incidents, such information includes the number and location of exposed persons, the thermal load associated with the fire event and the composition of the vehicle population. This information provides valuable knowledge with respect to the characteristics of the evolving fire scenario and facilitates the identification of efficient strategies for evacuation.

The main contribution of the present work comprises a probabilistic agent-based model, including different sources of information (prior and real-time), to assess the effect of first response risk reducing measures and to rank and plan evacuation operations. The probabilistic modeling and assessments take basis in information collected through real-time monitoring of the traffic. The developed models may readily be integrated in tunnel risk-assessment approaches, which considers escape conditions such in Schubert, et al. 2011 and/or ASTRA 89005.

2. CHARACTERISATION OF TUNNEL USERS

Losses in tunnel fire scenarios are not fully governed by the characteristics of the fire event in isolation but also critically depend on the operational conditions, smoke extraction and/or ventilation systems, emergency systems and evacuation facilities and finally but not least the behavior of the tunnel users at risk. Behavioral and social characterizations of tunnel users in dependency of the operational conditions at the time of fire events are generally not accounted for. Often, worst-case scenarios, where the exposed users are assumed to belong to the most vulnerable categories such as children, elderly and disabled persons, are assessed and used for the decision-making.

In the following, social characterization refers to the representation of users within a tunnel fire and/or evacuation scenario. Social characterizations may take basis in demographic characterizations of target groups of users and macro indicators such as societal composition with respect to gender, age and health characteristics of relevance for escape dynamics. The specific characteristics of the users of a given roadway tunnel in a given fire incident may be realized to originate from a mapping, or filtering of the characteristics of the general population which depends on e.g. geographical location, time of day and traffic composition.

Prior information such as demographical statistics and annual average daily traffic (AADT) curves are relevant sources of information for the modeling of the characteristics of vehicles and users. Real-time information with respect to the characteristics of the actual traffic and tunnel users, in the event of a fire, facilitates optimization of measures for loss reduction.

3. REAL-TIME AND PRIOR INFORMATION

Important characteristics of the operational conditions are provided through the AADT curve. This curve provides information with respect to the daily traffic demand variations and can be used to classify the regimes of operation and assign the type of the roadway tunnel. Whereas the AADT curve provides base knowledge on the expected daily traffic in general, a Real-Time Daily Traffic (RTDT) curve provides more relevant and precise information but coming with costs of installing, operating and maintaining a real-time traffic monitoring system.

In the bottom of Figure 1, a typical AADT curve is shown. Although the AADT curve provides best available knowledge from past tunnel operations, the estimation of the number of exposed persons based on the AADT would be different compared to any actual scenario. This is because the AADT represents average operational conditions. In Figure 1 (upper part), a comparison between the AADT and the RTDT curves is provided. The differences not only originate from averaging the number of vehicles over time but from the variations in composition of the vehicle population and the variation of the traffic volume at a particular time of the day and year.

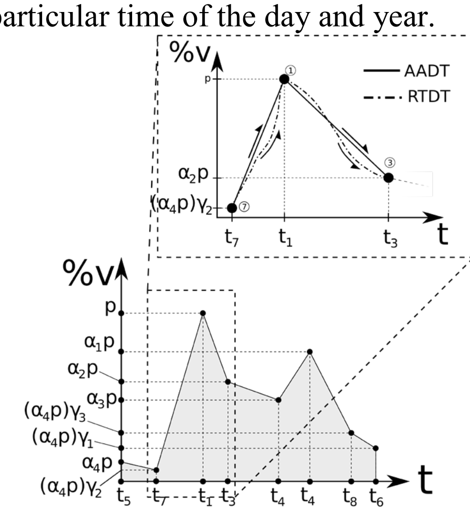


Figure 1. AADT curve and RTDT curve, both defined with vector of parameter $\tilde{\gamma}$ and $\tilde{\alpha}$ (see table B.1) in the operational time, t.

The AADT curve is only one example of how integration of real-time information may contribute to roadway tunnel risk management. In the risk assessment framework provided in ASTRA 89005 and Schubert et al. (2011) a variety of sources of information are combined. The framework proposed in ASTRA 89005 and Schubert et al. (2011) utilizes a Bayesian Probabilistic Network (BPN) representation of tunnel accident and fire event scenarios, and considers different evacuation options. Utilization of real-time information with respect to operational conditions facilitates optimization of decision support for the management of risks in roadway tunnels in the event of accidents and fires. A part of the BPN applied in ASTRA 89005 is illustrated in Figure 2.

The present research addresses specifically the part of the BPN shown in Figure 2, which models the exposure of persons in the tunnel system. To this end, a scheme is utilized combining probabilistic scenario based representations of the scenarios of accidents and fires with probabilistic agent-based modeling (societal exposure node), together with the RTDT curve (random operational context). The model is based on prior information about the tunnel as indicated by the nodes around the node named Escape in Figure 2.

4. INTEGRATION OF AGENT-BASED MODELING AND THE RTDT CURVE.

Agent-based modeling is widely used in fire engineering for the representation of the evacuation process; see Abar et al. 2017 and Ronchi et al. 2013. It is typical to simulate random population of users with random behavioral characteristics. A central safety requirement in fire risk management is that the evacuation time should be smaller than the smoke-fire spread time. Humanoid-agents (HA) are idealized mathematical representations of humans in the context of evacuation scenarios. The modelling of HA accounts for the interaction between static and non-static spatial elements such as walls, fire, smoke, HA-groups or simply other HA. Although, HA do not capture all aspects of human and social behavior in risk scenarios, such as grouping, social cohesion, decision making under stress, aiding and collaborative behavior, etc.; this is the presently most adequate modeling scheme for the representation of human behavior during evacuation scenarios. In the case of tunnel systems, the modeling of the HA must account for the specific characteristics of the users on the location at the time of the incident – demographic information - as highlighted previously.

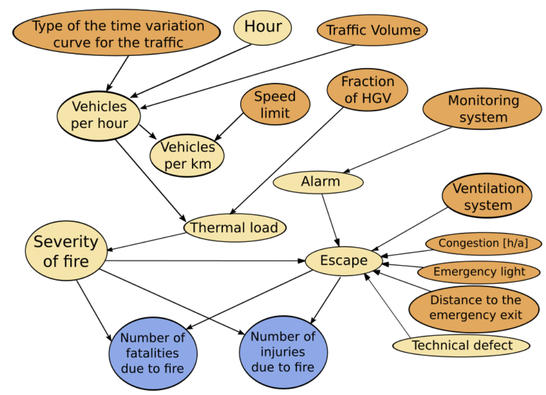


Figure 2. Extract of the BPN in ASTRA 89005.

Demographic information contributes to the modeling of behavioral characteristics of users at a particular location at a given time. The relative composition of young persons, adults, elderly or children may vary significantly from scenario to scenario and this may indeed effect the success of evacuation. This aspect of roadway tunnel risk management is generally neglected since the management of the composition of roadway users cannot be directly influenced. However, as shown in the example in Section 5 this type of information may greatly enhance decision making on first response loss reduction activities.

The users of roadway tunnel systems, i.e. the persons driving or being transported may be assigned to the different seats in the vehicles, e.g. in the driver seats only a specific group of persons may be located according to laws and rules concerning age, physical abilities and training. A simple scheme for the modeling of the location of HAs is shown in Figure 3. The HAs are simply placed in their respective seats in their vehicles. The vehicles present in the tunnel at the time of an incident can generally be allocated to specific classes of vehicles such as “normal passenger cars”, “busses” and “heavy-goods vehicles”. In order to integrate real-time and prior information into the BPN in Figure 2, a vehicle-cohort scheme is used, as indicated in Figure 4.

Once a fire incident is detected, the time of fire initiation t_{fire} is set. In the lower part of Figure 4, a segment of the RTDT curve is shown. Provided that the vehicles are observed and registered at the tunnel entrance, a reference population of tunnel users can be established. Moreover, a monitoring system installed inside the tunnel can potentially provide information related to the location of the fire at the detection time of the fire condition, t_{fire}.

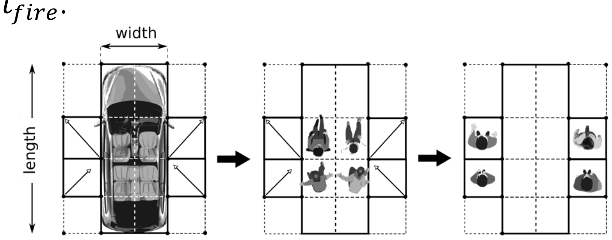


Figure 3. Co-location of humanoid-agents in the vehicle scope of population.

From the available information concerning fire detection time and location of fire, the arrival time Δ_{ref} and entrance time $t_{c1} = (t_{fire} - \Delta_{ref})$ may be established for the first cohort of vehicles in front of the incident zone. The first cohort is likely directly involved in the fire event i.e. the potential thermal load is originating from one or several of the vehicles of this cohort.

From the available information, the amount and types of vehicles in the n segments $(i_{c1}, i_{c2}, \ldots, i_{cn})$ (see Figure 4) of the tunnel may finally be established and on this basis measures of risk control may be initiated, e.g. extinguishing systems, stop vehicle inflow, call rescue and risk management groups, etc.

5. APPLICATION EXAMPLE

The Fehmarn-Belt Tunnel is used as basis for the following example to illustrate the suggested modelling approach. This tunnel project that is planned for commencement in 2020; will be the world's longest immersed rail-roadway tunnel with a total length of 18 km. In this example focus is directed on the assessment of the risk reducing effects of timely restriction of vehicle inflow in case of a tunnel fire scenario w. Real-time monitoring information is obtained in the form of a RTDT curve, based on the prior information provided in Table B.1 in Appendix B.

The quantification of the exposure of tunnel users is facilitated through the evacuation curves of the simulated scenarios as indicated in Figure 5.a. The restriction of vehicle inflow obviously leads to the reduction of users in the fire incident but does not provide a precise indicator of user exposure and behavior in the course of evacuation. In other words, control measures affecting the number of users and their location will affect their exposure to the fire scenario only in dependency of their behavior. The risk reducing effect depends on the decisions, which in turn depend on the specific characteristics of the fire event scenario and the number, placement and types of vehicles, together with the specific layout of tunnel (exit door distance and safety facilities). Agent-based modeling facilitates the modeling of these effects.

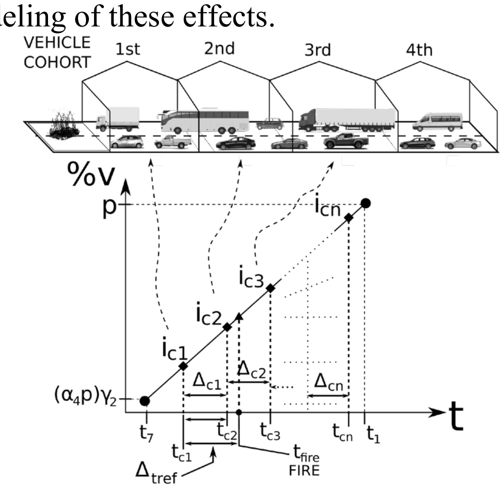


Figure 4. Real-time daily traffic curve and intervention strategy.

For the application example, the random and deterministic variables are provided in Table B.1. The physical characteristics of the tunnel are shown in Figure A.1 in appendix A. Two groups of simulations are compared: drill-evacuation dynamics (see Figure C.1 in appendix C, with the detection-reaction curve of the users) and fire-evacuation dynamics (see Figure C.1 in appendix C, with the heat release rate curve of the fire source). The scenario of drill-evacuation dynamics refers to the process of evacuation in the absence of fires. The fire-evacuation process refers to the inclusion of fire in the scenario in which HAs interact with both the fire event and other HAs. In each of the previous groups, three scenarios are considered corresponding to the effect of reducing vehicle inflow, namely: 100%, 75% and 50% of the random vehicle population in a simulation window corresponding to $w = 500$ m from the location of the fire incident, for a given

RTDT curve at a specific time during daytime operation (see table B.1). For each scenario, 30 random operational scenarios are simulated using Monte Carlo simulation to obtain the data specifying the locations of the HAs and the dynamics of the evacuation after the detection of the fire. After the probabilistic simulation, the evacuation curves are calculated of each of the 180 scenarios.

HA's are characterized as described in Section 3 with the variables given Table B.1. Physical-social and behavioral features interact with the HA's in the tunnel structure during evacuation.

6. RESULTS

The chosen simulated scenarios at 8:00 am show that the scenario with no reduction of vehicles (100% case) has a mean of 240 users with a standard deviation of 16. When a reduction of vehicles is 25%, through inflow control, the number of tunnel users has a mean of 180 users (75% case) with a standard deviation of 26. Finally, reducing the number of vehicle to 50% results in a mean value of 140 users (58 %) with a standard deviation of 45 (50% case).

The curves in Figure 5-a show the evacuation curve without fire. The gray lines represent the 30 simulation in the case of evacuation-drill. The solid black lines refers to the expected values and the broken lines correspond to the standard deviations.

In the figures 5-b, 6 and 7, the solid lines represents the case of no reduction of vehicles (100% of vehicles), the segmented lines corresponds to a reduction of vehicle inflow by 75% of vehicles and segmented–dotted lines a reduction of 50% of vehicles. In the mentioned figures, black colors refers to fire-evacuation dynamics and gray color refers to drill-evacuation dynamics.

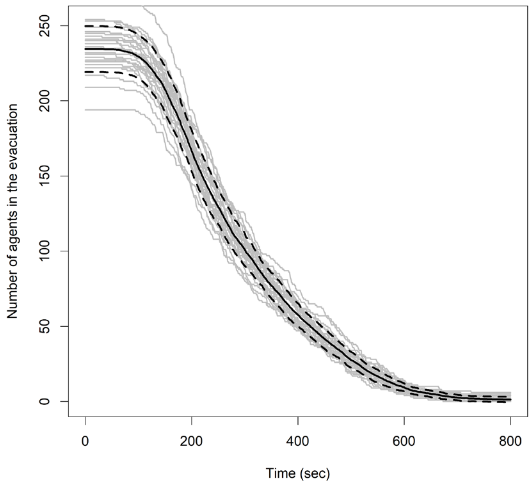
A comparison of the simulation with and without fire is shown in Figure 5-b. The differences for the two cases are rather moderate for what concerns the mean value. This figure is showing the influence of the detection capability of the HAs according the assigned detection threshold (mg/m^3 of the hazardous substance) and the applied detection parameters (see Figure C.1 in Appendix C).

In Figure 6, the coefficient of variations (COV) of the drill-evacuation and fire-evacuation are compared. When the COV is calculated for each time interval, large differences are observed, see Figure 6. The results shown in Figure 6 indicate that evacuation scenarios involving smaller numbers of HA are less stable and result in an increased value of the COV. This effect is caused by the situation that in such scenarios fewer interactions between the users take place. Scenarios with more actors on the other hand stabilize the evacuation process and reduce the COV. Although HA's realize the fire event earlier (Figure 5-b), the development of the scenario can be more unstable due to different not identified conditions, e.g. vision in the tunnel, decision of exit door, toxicity rate, etc. A closer view on the evacuation process 500 seconds after fire ignition is provided in Figure 7 with the estimated distributions of the number of evacuated HAs over this period of time.

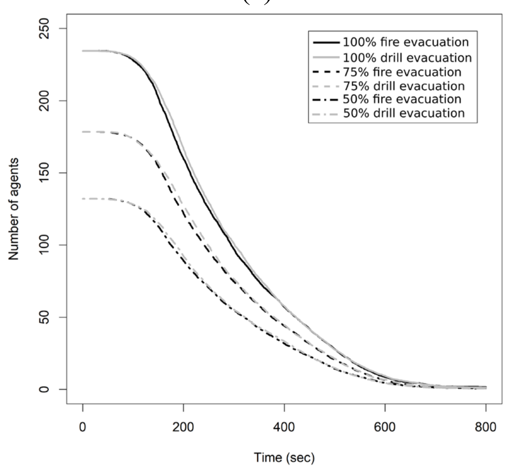
7. CONCLUSION

This paper presents a probabilistic model of scenarios leading to accident and fires and subsequent evacuation of persons in roadway tunnels. The proposed modelling approach is developed and illustrated in the context of the Fehmarn-Belt Roadway Tunnel, considering monitoring options and utilization of real-time traffic and fire event scenario monitoring systems. It should be underlined that the applied models have not been based on those, which are relevant for the final design of the Fehmarn-Belt Tunnel systems. The results of the present paper are thus not in any manner related with the design or operation of the actual Fehmarn-Belt project.

The effects of behavioral aspects of tunnel users during evacuation are represented through agent based modelling. Two categories of cases are considered: drill-evacuation dynamics and fire-evacuation dynamics. For each catagory, three cases are explored: No action taken to reduce the inflow of vehicles after the event of a fire is initiated, reduction of inflow of vehicles by 75% and reduction of inflow of vehicles by 50%.



(a)



(b)

Figure 5 – Number of humanoid-agents in the simulation. (a) Evacuation curve for 100% of vehicles in drilling-evacuation dynamic. (b) Comparison between evacuation-drilling dynamic and fire-evacuation processes.

While the reduction of users in the tunnel system during the fire event closely follows the reduction of vehicles in the fire scenario, the COV associated with evacuated persons is found to increase. This tendency might be attributed to spatial effects such as the location and spread of vehicles, social-behavioral as well as the physical characteristics of the HA's. Future efforts should be directed to investigate these effects in more detail.

8. ACKNOWLEDGMENT

This work is part of *Femern SafetyLab Project*, funded by the Danish Agency for Science and Higher Education.

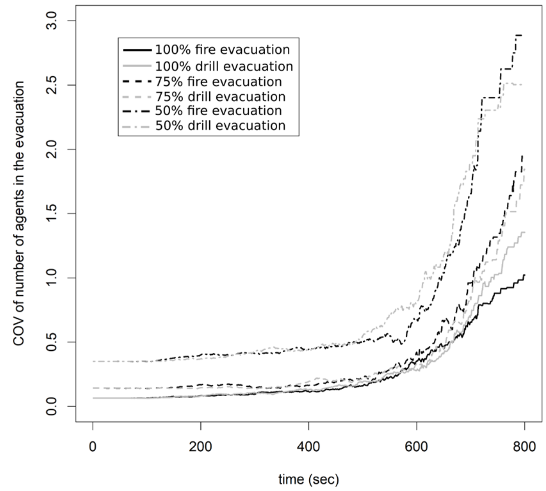


Figure 6. COV Comparison of evacuation-drilling dynamic and fire-evacuation cases.

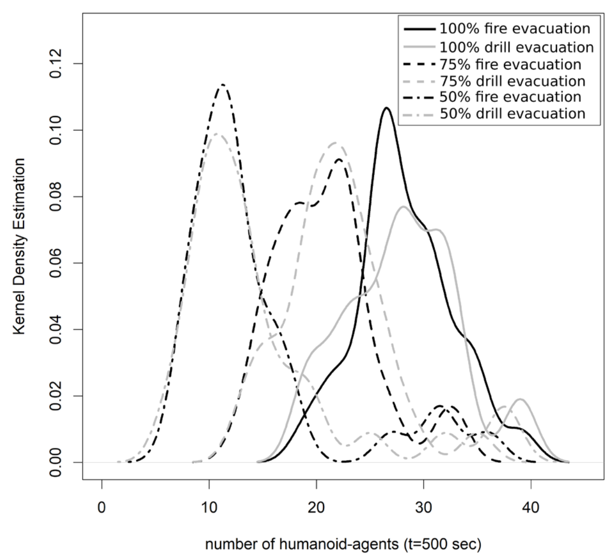


Figure 7. Density estimation of probability density function of humanoid-agents in the simulation window, 500 seconds after the fire occurrence.

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APPENDIX A. TUNNEL PHYSICAL ARRANGEMENT

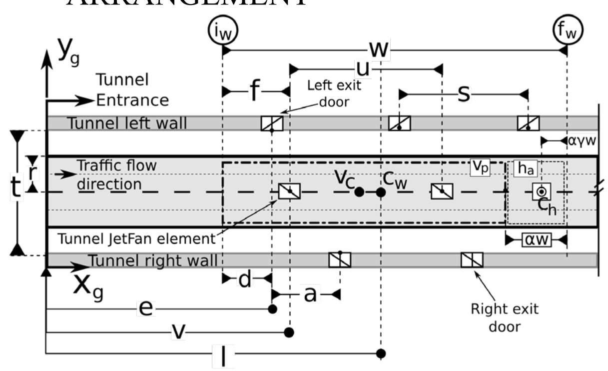

Figure A.1 – Tunnel spatial context.

APPENDIX B. THE PROBABILISTIC SIMULATION INFORMATION

Table B.1 – Stochastic and deterministic variables of the probabilistic simulation.

Num	Var.	Distribution/value and description
1	w	D /500 m - Simulation window or the length of chosen segment of the tunnel at a specific location for simulation purposes.
2	s	D / 110 m - Separation between exit doors (in both sides of the tunnel).
3	u	D/400 m - Separation between ventilation elements within w.
4	α	MN~prior knowledge [{22.5, 27.5, 32.5, 37.5}, {0.3, 0.4, 0.25, 0.05}] - Ratio between the length of h_a and the windows length w . Also, understood as the percentage of the hazard influence area h_a within the window w.
5	γ	MN ~ prior knowledge [{0.05, 0.15, 0.25}, {0.4, 0.4, 0.2}] - Ratio between the distance of the center of the hazardous agent c_h (taken from f_w) and α.
6	r	D / 4 m - Given lane width for simulation purposes
7	t	D / 11 m - Tunnel road width considering side shoulders and lanes
8	n_{sim}	30 per study case (180 in total) - Number of simulation or stochastic samples of tunnel cases.
9	t_l	D / 18000 m - Tunnel total length
10	t_{ih}	D / 5.2 m - Height of the tunnel in the simulation
11	t_{lew}	D / 0.5 m - Thickness of the left-side external wall
12	t_{rew}	D / 0.5 m - Thickness of the right-side external wall
13	t_{liw}	D / 0.5 m - Thickness of the left-side internal wall

14	t_{riw}	D / 0.5 m - Thickness of the right-side internal wall
15	e_{rl}	D / 4.5 m - Right-side exit lane
16	e_{ll}	D / 4.5 m - Left-side exit lane
17	n_l	2 (uni-directional) - Number of lanes
18	d_w	D / 2 m - Width of exit doors (left and right side doors).
19	d_h	D / 2.1 m - Height of exit doors (left and right side doors).
20	v_{nf}	D / 3 m - Number of ventilation fans in each ventilation element (group of jet-fans in a perpendicular line to tunnel length).
21	s_j	D / 0.5 m – Side space between jet-fans.
22	v_{nps}	D/10 - Number of segments of passenger vehicles, see table B.2 in de appendix B.
23	v_{nhg}	D/ 21 - Number of segments or types of heavy-goods vehicles, see table B.2 in de appendix B.
24	a_t	D / {2 (50%),3 (75%),4 (100%)} - Number of vehicle cohorts that have arrived to the window-segment
25	a_{ppp}	1.43 - Average passenger per vehicle 2017 according the European Environment Agency.
26	$\tilde{b}_{up}$	MN ~ prior knowledge [{0.05, 0.15, 0.25 }, {0.4, 0.4, 0.2}] - Matrix with given behavior pattern for vehicle passengers, with dimensions $[n_{tv} \times n_{seat} \times n_{pa}]$, where n_{tv} is the total number of vehicles in the simulation, n_{seat} is the number of available seat in the vehicle and n_{pa} is the number of passengers in the vehicle. The following letter are considering the different behaviors; A= Active, C= Conservative, H= Herding and F= Follower for more detail see ref. [Korhonen, 2011]
27	$\tilde{g}_{s1a}$	MN ~ prior knowledge [{AD, MA, FE, EL,CH; AD, MA, FE, EL, CH; AD, MA,FE, EL, CH; AD,MA, FE,EL, CH; }, {0.4, 0.2, 0.2, 0.2,0.0}; {0.25, 0.25,0.25, 0.25, 0.0}; {0.2, 0.2, 0.2, 0.2, 0.2}; {0.2, 0.2, 0.2, 0.2, 0.2}] - Matrix with physical properties (body shape, age, gender), e.g. “MA”=Male, “FE”= female, “AD”= Adult, “EL”= Elderly and “CH”= Child. Matrix with dimensions $[n_{tv} \times n_{seat} \times n_{pa}]$, where n_{tv} is the total number of vehicles in the simulation, n_{seat} is the number of available seat in the vehicle and n_{pa} is the number of passengers in the vehicle For details related with physical properties see ref. [Helbing and Molnár, 1995]
28	Passenger vehicles	MN ~ prior knowledge [{ Mini cars , Small vehicles, Medium cars – small family vehicles, Large cars – Large family vehicles, Executive vehicles, Luxury vehicles, Sport vehicles, Multi-purpose vehicles, SUV and off-roads vehicles, Others (Bus/Coach) }, {0.08, 0.24, 0.3, 0.07, 0.03, 0.005, 0.02, 0.35, 0.2, 0.02}] - Prior knowledge of passenger vehicle population per segment. European Vehicle Market Statistics Pocketbook 2017/18.
29	Fraction of Heavy-good vehicles	MN ~ prior knowledge [{Box Van,Tipper Truck, Curtain sided vehicle, Drop side Lorry, Flat Lorry, Refuse disposal truck, Insulated Van, Skip loader vehicle, Tanker, Panel Van, Street Cleasing vehicle, Car Transporter vehicle, Concrete Mixer, Live Stock Carrier, Heavy-Goods transporter, Tractor, Skeletal Vehicle, Tower Wagon, Motorhome, Luton Van, Others}, {0.2305, 0.1452, 0.1263, 0.0767, 0.0699, 0.0624,0.0496,0.0481,0.0299,0.0217,0.0189,0.0185,0.0167,0.0160,0.0092,0.0082,0.0067,0.0064,0.0064,0.0039,0.0278}] - Prior knowledge of passenger vehicle population. From Transport statistics bulletin: Road Freight Statistics 2010. Department for transport, national statistics publication, London.
30	RTDT $\tilde{\gamma}$ *and* $\tilde{\alpha}$	U / [TYPE F (see Schubert et al. 2011) - Real-Time Daily Traffic parameters of the curve: $1.95 \leq \alpha_1 \leq 2.1$, $1.07 \leq \alpha_2 \leq 1.1$, $1.1 \leq \alpha_3 \leq 1.2$, $0.04 \leq \alpha_4 \leq 0.06$, $1.8 \leq \gamma_1 \leq 2.1$, $0.25 \leq \gamma_2 \leq 0.61$, $3.6 \leq \gamma_3 \leq 4.2$]
31	t_{dt}	D / 8 am – Daytime
32	S_{lim}	MN~prior knowledge [{40, 50, 60, 70, 80, 90, 100, 110,120 ,{ 0.01, 0.00, 0.01, 0.00, 0.50, 0.00, 0.46,0.00,0.02 }] - Speed limits
33	v_{pk}	As in ASTRA 89005 and Schubert et al. 2011 - Vehicles per kilometer
D=Deterministic, U=Uniform, MN=Multinomial distribution.		

APPENDIX C. DETECTION-REACTION AND HEAT RELEASE RATE CURVES.

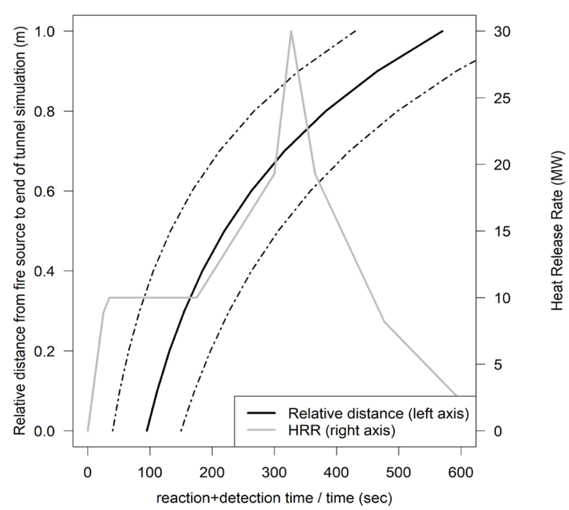

Figure C.1. Mean value of the detection and Reaction Curve (solid black line), standard deviation of detection and reaction curve (segmented black line) and Heat release rate curve in gray.